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DO WAITING TIMES MATTER IN PRIMARY CARE? GP VISITS AND LIST SIZES IN ENGLAND*

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This paper is largely motivated by the empirical observation that GP visits per person under the NHS have increased in England since the mid-1970s, while list sizes have decreased over the same period. A hypothesis consistent with this observation is that larger list sizes are associated with longer waiting times, which reduce the demand for GP visits. Using a time series of repeated cross sections from 1972 to 2004, we construct a pseudopanel of synthetic individuals and find very little evidence that list sizes affect visit frequencies. While there are mild associations consistent with the waiting-time hypothesis among working-age women, there are none for men or the elderly, and no associations are robust to the cohort analysis. The demand for GP visits is most likely driven by health status, and for women, childbirth.

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1. INTRODUCTION

A large health economics literature has investigated how time-money tradeoffs operate primarily within markets for non-urgent secondary and tertiary medical care, which include inpatient and outpatient hospital visits, specialist consultations, elective and non-elective surgeries, and so on. A synthesis is given by Cullis et al. (2000). However, these tradeoffs are less frequently investigated within a primary care setting, and this paper aims to fill that gap empirically.

There are primarily two economic approaches to waiting times in medicine. The first is queueing theory. Within a general equilibrium framework, waiting times are the "prices" associated with hassle and delay that are sufficient for markets to clear (see, for example, Lindsay and Feigenbaum (1984), Cullis and Jones (1986), Goddard et al. (1995), Iversen (1997), and Martin and Smith (1999)). Waiting lowers the value of medical care for consumers due to simple time preference and treatment decay, where the latter is a central feature of this class of models. Treatments decay because they are worth less with delay. Note, however, that queueing by list does not affect the time constraint since it does not preclude the consumer from engaging in market and non-market activities. A consumer then joins a list if the net present value of doing so exceeds the net present cost. Interacted with supply (see, for example, Iversen (1993) for a treatment of the provision of medical services), this gives rise to a general equilibrium, from which the derivable comparative statics of interest are that the rate of joining a list is increasing in the value of public medical care and price of private medical care, and decreasing in the value of private medical care, expected waiting time, and rate of decay.

A second class of models considers the effects of time costs, which operate directly through the time constraint in the form of lost market and non-market opportunities, on the demand for medical services (see, for example, Acton (1975), Coffey (1983), and Phelps and Newhouse (1974)). The relevant implication is again an inverse relationship between time costs and demand, but the mechanism is distinct from any decay associated with queueing.

Empirical work in this area is largely restricted to the United Kingdom (UK), where the medical economy has been mixed since the National Health Service (NHS) began formal operation in 1948. The NHS aims to provide population-level medical care, balancing universal coverage, individual responsiveness, and cost effectiveness. It is funded largely through progressive taxation. Since all NHS services are universally accessible and free at the point of delivery, waiting for medical care is a common experience at many levels, and waiting lists and waiting times receive high priority among researchers, policymakers, and government officials. A private sector operates alongside the NHS and delivers medical care that is unprovided or under-provided in the public sector. It is either paid for out-of-pocket or covered by private health insurance companies, both for-profit and not-for-profit, and plans are negotiated individually or through employers.

Several studies from the UK have empirically corroborated, to varying degrees, some of the comparative statics implied by theories of waiting. Since waiting times and prices are both endogenous in these equilibrium models, any empirical analysis requires valid and informative instruments for estimation to be consistent. Instruments for waiting time are typically exogenous supply variables, such as the number of doctors or the number of hospital beds in a given region. Lindsay and Feigenbaum (1984) find a negative correlation between the rate of joining a list for hospital services and delay, which is made more pronounced when the rate of decay is high. Gravelle et al. (2002) show that admission rates for cataract procedures are negatively correlated with waiting times. Martin and Smith (1999) estimate a low elasticity of demand for elective surgeries with respect to waiting time, and ultimately conclude that free medical services can be extended in order to reduce waiting times with only a trivial stimulation of consumer demand. Martin et al. (2007) further demonstrate that longer waiting times for non-emergency surgeries reduce demand only very slightly. These empirical studies have shown that public demands tend to be relatively inelastic with respect to waiting times. Besley et al. (1999) find that longer waiting lists for NHS treatment are associated with greater purchases of private health insurance, suggesting that longer waiting times shift demand from the public sector to the private sector. However, Martin and Smith (1999) show that private alternatives have little effect on the public demand for elective surgeries, suggesting that private sector prices do not shift demand towards the public sector.

The conventional economic approach has been to assume equilibrium. However, where demand exceeds supply and vice versa, there is disequilibrium, in which case observed prices, waiting times, and service rates are not those which are required for markets to clear. However, if one holds this assumption erroneously, then the model is misidentified. Blundell and Windmeijer (2000) estimate a model of equilibrium demand for acute hospital care that is robust to disequilibrium by selecting areas with low waiting times and then correcting for endogenous selection. In these areas, they find no evidence of a relationship between waiting times and consumer demand.

Propper (1990, 1995) argues the further position that waiting results in a disutility that is independent of either decay or time costs. This disutility is related to the consumer's poor health, uncertainty about the length of the wait, and anxiety over the health outcome. If queueing by list does not affect market and non-market potential, then for illnesses with non-decaying treatments, the costs of waiting should be zero according to the existing frameworks. However, this prediction has been been met with skepticism empirically.

To briefly summarize, while waiting times may affect consumer demand through several plausible mechanisms, most notably via treatment decay and time costs, there is nonetheless a consensus view as to the relevant comparative statics. Of primary interest are the results that longer waiting times reduce public demand and induce private demand. These predictions have been corroborated by many, but certainly not all, empirical studies.

While these time-money tradeoffs are relatively well documented within markets for secondary and tertiary care, they are less frequently investigated within a primary care setting, which is the caretaking face of a health system and the gateway to further care. This paper is largely motivated by the empirical observation that general practitioner (GP) visits per person under the NHS have increased in England since the mid-1970s, while list sizes have decreased over the same period. A hypothesis consistent with this observation is that larger list sizes are associated with longer waiting times, which reduce the demand for GP visits. Using a time series of repeated cross sections from 1972 to 2004, we construct a pseudopanel of synthetic individuals and find very little evidence that list sizes affect visit frequencies. While there are mild associations consistent with the waiting-time hypothesis among working-age women, there are none for men or the elderly, and no associations are robust to the cohort analysis. The demand for GP visits is most likely driven by health status, and for women, childbirth.

The organization of this paper is as follows. Section 2 provides some empirical background. Section 3 outlines the implementation. Section 4 presents the results. Section 5 concludes.

2. BACKGROUND

2.1. *Data*

The data on individuals and GP visits are from the General Household Survey (GHS) from 1972 to 2004. These data include both demographic and health characteristics, as well as information about the use of health services. We use data from the GHS rather than the British Household Panel Survey (BHPS) or the Health Survey for England (HSE) in order to exploit variations in GP visits and list sizes that occur prior to 1991, the year during which both the BHPS and HSE were launched. However, we note that the alternatives have some obvious advantages. The BHPS is a panel, which facilitates controlling for time-invariant unobserved heterogeneity, and the HSE contains more detailed information on health status.

The GHS has surveyed a representative sample of the UK population since 1971. We make use of a time series of repeated GHS cross sections from 1972 to 2004, which was recently deposited in the UK Data Archive. However, critical GP visit data are missing in 1971, 1972, 1977, and 1982, data are inconsistent across sources in 1973, and critical health status data are missing in 1978. Furthermore, the GHS was not conducted in 1997 and 1999. We are therefore left with 26 time points. Over this lengthy period, the Office for National Statistics (ONS) surveyed a representative sample of 296,824 UK households and 756,769 individuals within these households. The household questions are addressed to the household reference person, capturing information on demographics, family structure, accommodation, housing tenure, ownership of consumer durables, migration, and income. The individual questions are addressed to all individuals 16 and older within each household, capturing information on employment, pensions, education, health, the use of health services, fertility, and income.

The data on GPs are from the Department of Health (DoH) and the NHS Information Centre (IC). The DoH and IC provide list sizes, which are the number of registered patients divided by the number of public GPs in a given area. In the numerator, we use the number of registered patients rather than the corresponding population estimate in order to more effectively capture congestion. However, we note that the number of registered patients typically exceeds the corresponding population estimate, resulting in an inflation of list sizes that is not necessarily randomly distributed across areas or over time. In the denominator, we adopt a GP head count rather than a full-time equivalent (FTE) measure primarily for two reasons: (1) to achieve greater continuity over time, and (2) to avoid using FTE scales based on data from the early 1990s. However, we note that some GPs only work part-time and that other health professionals, not included in the workforce count, sometimes take on GP-like roles, resulting in a deflation and inflation of list sizes, respectively, that are again not necessarily randomly distributed across areas or over time.

In order to link list sizes to individuals in the GHS sample, we use Government Office Region (GOR), which corresponds to Northeast, Northwest, Yorkshire and the Humberside, East Midlands, West Midlands, East, London, Southeast, or Southwest. We have restricted our scope to England since the disaggregated GP data we require are not available for Scotland, Wales, and Northern Ireland. These exclusions also eliminate the need to address further confounding regional and cultural effects.

In the data, we observe the number of GP visits over a two-week period, and in recent years, whether these visits are covered by the NHS or paid for privately. GP consultations are almost exclusively covered by the NHS throughout the period we study. A private sector emerges in the data beginning in the early 1990s, but the great majority of GP visits continue to occur publicly. In this paper, we only consider public sector visits. Lastly, we restrict our attention to visits made solely on the behalves of the respondents, excluding consultations by telephone and at home. Since the sample period is only two weeks, we mainly observe respondents reporting either zero visits or one visit. We drop outliers reporting 7 or more visits.

The GHS contains standard demographic variables, some of which have been cited as powerful determinants of GP consultation patterns (see, for example, Bago d'Uva (2005) and Carr-Hill et al. (1996)). We observe each individual's age, sex, and marital status, where the latter allows us to classify individuals as never married, married, separated, divorced, or widowed.

The GHS also provides a variety of data on health. In order to avoid relying upon self-assessments of health as much as possible, we use chronic illness information to capture health status. While limited in scope, this variable suffers from less measurement error and has fewer missing values than the alternatives, and it is more reliably compared across individuals. Nonetheless, we acknowledge that other health measures (e.g., self-assessments, diagnoses, physical limitations) may have independent explanatory power.

Unfortunately, the GHS does not provide income and education data that are reliable and consistent over time. The survey questions have become increasingly sophisticated and complex, which sometimes results in a high proportion of missing values and data that are less directly comparable over time. We recognize the obvious omitted variable problems created by theses exclusions—in particular, if income and education are both negatively correlated with chronic illness, then our results will overstate the illness effect if income and education are negatively associated with GP visits, and vice versa if they are positively associated.

Further details about the data and empirical variables are provided in Appendix A.

2.2. *Motivation*

Data from the GHS show that for working-age and elderly individuals in England, the probability of visiting a GP at least once in two weeks has increased from 12.7 to 16.4 percent between 1974 and 2004. We define working-age as 16 to 65 and elderly as 65 and older. From these self-reported consultation data we can construct estimates of the average number of annual GP visits per person. For a given year, averaging the number of GP visits in two weeks across thousands of individuals surveyed uniformly across the months of the year and multiplying by 26 gives the consistent estimate that we desire. The average number of annual GP visits per person has also increased between 1974 and 2004. Figure 1 highlights GP visit trends for working-age women and men, as well as elderly women and men. Note that the patterns are similar for working-age women, elderly women, and elderly men. The average number of annual visits has increased from 4.5 to 6.3 for working-age women, 4.8 to 7.4 for elderly women, and 4.9 to 6.7 for elderly men, corresponding to average increases of about

1.1, 1.5, and 1.0 percent per year, respectively. However, working-age men visit their GPs much less frequently and with a less pronounced rate of increase over time. The average number of annual visits has increased from 3.3 to 3.8 for working-age men, corresponding to an average increase of about 0.5 percent per year.

[Figure 1 about here]

There are several plausible explanations for these trends (see, for example, Fitzpatrick and Chandola (2000) for a recent survey and references, as well as Bago d'Uva (2005) and Carr-Hill et al. (1996) for demographic and socioeconomic determinants specific to primary care). Firstly, if the population is growing older over this period, then the number of GP visits may have grown as well since older people are generally in worse health and have a greater need for medical care (see, for example, Coleman (2000) for a recent summary of demographic trends). Secondly, over time GPs may have been accommodating an increasing share of a case-mix which formerly sought hospital treatment. Since the capacity to diagnose, treat, and monitor complex illness has increasingly become the domain of the GP, a burden of disease may have shifted away from the hospital and towards the clinic. Thirdly, if people have become more accustomed to the NHS over time, then they may also have become better equipped to utilize any services available to them, controlling for any changes in the services themselves. However, since the NHS began formal operation in 1948, more than 25 years before our period of observation begins, we expect this effect to be relatively small. Fourthly, attitudes towards health, especially given the increasing availability of public information, may have changed over this period, giving rise to an increase in general preventive awareness. Fifthly, with non-satiated demands for GP visits and decreasing visit costs, the number of GP visits per person may have grown in response to relative price changes.

[Figure 2 about here]

The final explanation is the subject of this paper. As data from the DoH and IC show in Figure 2, the average list size in England has decreased from 2,384 to 1,666 between 1974 and 2004, an average decrease of about 1.2 percent per year. Decreasing list size is a result of the number of GPs increasing faster than the population, and hence the number of registered patients. In this paper we explore nonstructurally how Figure 2 relates to Figure 1. While we hesitate to make any causal claims, we hypothesize that larger list sizes correspond to longer waiting times, which reduce the demand for public GP visits, and vice versa. See Polisson (2009) for a structural interpretation.

3. IMPLEMENTATION

The most relevant comparative static from theories of waiting times implies that GP visits are negatively correlated with list sizes. The reduced form that we want to estimate is then

$$v_{it} = \alpha + \beta' x_{it} + \gamma(list_{it}) + \theta_i + \mu_t + \epsilon_{it}, \tag{3.1}$$

where $v_{it} \in \mathcal{R}_+$ is the number of annual GP visits, $\alpha \in \mathcal{R}$ is an intercept parameter, $x_{it} \in \mathcal{R}^K$ are observed characteristics with corresponding parameters $\beta \in \mathcal{R}^K$, $list_{it} \in \mathcal{R}_{++}$ is list size with corresponding parameter $\gamma \in \mathcal{R}$, $\theta_i \in \mathcal{R}$ is an individual-specific fixed effect, $\mu_t \in \mathcal{R}$ is a time-specific fixed effect, and $\epsilon_{it} \in \mathcal{R}$ is an unobserved idiosyncratic error term, distributed normally with mean zero and variance $\sigma^2 \in \mathcal{R}_{++}$. We let $i \in \{1, \ldots, N\}$ index each individual and $t \in \{1, \ldots, T\}$ index each period.

The advantages of using panel data are well known. Panel data allow us to explore dynamics and to control for unobserved heterogeneity that is time-invariant. Identification is made possible with fewer restrictive assumptions than with cross-sectional data. However, in the absence of panel data, or when panels are short, systematically incomplete, or suffering from attrition, there is a well-established empirical alternative. The pseudopanel technique is first suggested by Deaton (1985) and put to empirical use by Browning et al. (1985). With many repeated and independent cross sections, Deaton (1985) suggests constructing cohorts of fixed membership and using sample cohort means as synthetic panel data. In a specification that is linear in its parameters, standard estimators are consistent but subject to measurement error bias. This occurs because sample cohort means are consistent estimators of population cohort means, but error-ridden in finite samples. However, using sample variances and covariances of the sample cohort means, errors-in-variables estimators allow for consistent estimation even in finite samples.

The GHS is not a panel since it does not follow individuals over time. Nonetheless, it captures a random sample of the UK population nearly every year. Although we cannot follow individuals, we can follow cohorts, and therefore we can construct synthetic individuals. Stable cohorts are defined by sex, year of birth, and GOR. A critical criterion for pseudopanels is that cohorts have fixed membership. While an individual's sex and year of birth are time-invariant, he or she may move across GORs over the course of his or her lifetime. In this paper, we assume that the effects of internal migration are relatively trivial, which we acknowledge as a potential source of bias (see, for example, Norman et al. (2005) for a discussion of health and migration). The safest and strongest assumption is to assume that these migrations are random and uncorrelated with any of the regressors in (3.1). While potentially problematic, using GORs to define cohorts gives rise to the variations in GP visit frequencies and list sizes across synthetic individuals that we exploit empirically. Figures 3 and 4 highlight the variability in levels and rates of change across GORs.

[Figure 3 about here]

[Figure 4 about here]

Defining cohorts requires that we trade off between cell sizes and the number of synthetic observations. Larger cell sizes produce less measurement error in the synthetic data but less precision in the panel estimates. Without an established method to define optimal cohorts, we follow trends established in the literature and aim for a mean cell size of about 150. We use ten-year age bands, individuals 16–25, 26–35, 36–45, and 46–55 in 1974, which correspond to years of birth in 1949–1958, 1939–1948, 1929–1938, and 1919–1928, respectively. Consequently, the youngest respondent in the raw sample is 16, and the oldest is 85. With four age bands, two sexes, and 9 GORs, we observe 72 cohorts over 26 years, which gives rise to 1,872 synthetic observations.

[Table I about here]

The data structure is presented in Table I. The mean number of individuals used to generate each synthetic observation is 139.5 with a standard deviation of 71.0. The median number is 126, with a minimum of 21 and a maximum of 442. There are 72 synthetic observations generated from less than 50 points, which represents 3.8 percent of the 1,872 synthetic observations. For this subgroup the mean number of individuals used to generate each synthetic observation is 41.3 with a standard deviation of 6.8. The median number is 43, with a minimum of 21 and a maximum of 49. We assume that our cell sizes are sufficiently large to generate estimates robust to measurement error biases.

Consider the population relationship in (3.1). Dividing the population into cohorts indexed by $c \in \{1, \ldots, C\}$ and averaging gives

$$v_{ct} = \alpha + \beta' x_{ct} + \gamma(list_{ct}) + \theta_c + \mu_{ct} + \epsilon_{ct}, \tag{3.2}$$

where $(v_{ct}, x_{ct}, list_{ct}, \mu_{ct}, \epsilon_{ct})$ are unobserved cohort population means and θ_c is the unobserved cohort fixed effect. Since we do not observe cohort population means, we use error-ridden sample cohort means. Since sample cohort means are consistent estimators of population cohort means, and since our cells are sufficiently large, we assume that standard estimation is robust to measurement error bias. The unobserved idiosyncratic cohort error term $\epsilon_{ct} \in \mathcal{R}$ is distributed normally with mean zero and variance $\varsigma^2 \in \mathcal{R}_{++}$. We assume ϵ_{ct} is independently and identically distributed, homoskedastic, and uncorrelated with the regressors. Since cohorts are different sizes, we weight each synthetic observation by the square root of the cohort size, which has negligible effects on both estimation and inference.

The relationship in (3.2) is easily estimated using the within-groups (WG) panel data estimator. In the presence of true fixed effects, the pooled ordinary least squares (OLS) estimator, between-groups estimator (BG), and random effects (RE) estimator are all inconsistent. While the first-differences (FD) estimator is consistent, it is not as efficient as the consistent WG estimator with a large number of time points. See, for example, Baltagi (2005), Cameron and Trivedi (2005), and Verbeek (1992) for the relevant econometrics. In practice, we first estimate the parameters using pooled OLS and then introduce dummy variables to capture cohort effects and age effects, testing for joint significance.

4. RESULTS

4.1. *Pooled Analysis*

Increasing GP visits and decreasing list sizes in Figures 1 and 2 have motivated this research. Table II provides further aggregated support. The average number of annual GP visits per person has increased between 1974 and 2004. The increase is most pronounced in the 1970s and 1980s, after which it flattens in the 1990s and even decreases slightly in the 2000s. The population and hence the number of registered patients have increased steadily over this period as well. As a consequence, the total number of GP visits has increased. However, the number of GPs has also increased steadily between 1974 and 2004, at a rate faster than both registered patients and total visits. The result is that list sizes and the average number of annual visits per GP have both decreased.

[Table II about here]

We interpret these crude findings as a relaxation of supply-side constraints. Decreasing list sizes mean that there were more GPs per person in 2004 than in 1974. Furthermore, fewer visits per GP means that workloads have become more manageable. The slackening of these constraints provides the variation that we exploit empirically when considering the relationship between waiting times, instrumented for by list sizes, and GP visits.

[Table III about here]

Summary statistics for our sample are reported in Table III. Working-age women, working-age men, elderly women, and elderly men are proportionally stable over time, with corresponding sample shares of 33.5, 31.8, 8.6, and 6.1 percent, respectively. Working-age women and men are about the same age, but elderly women are slightly older than elderly men. All cohorts are getting older over time, which is slightly more pronounced for men than women. Working-age women and men are equally likely to be married, but elderly men are much more likely to be married than elderly women. Smaller shares of working-age women and men are married over time, a trend well-established in the sociological literature (see, for example, Coleman (2000)). Elderly women are more likely to be married over time, and elderly men slightly less likely. Furthermore, both working-age and elderly women are much more likely than their respective male counterparts to be separated, divorced, or widowed. However, larger shares of working-age women and men and smaller shares of elderly women are separated, divorced, or widowed over time. In general, marital status among elderly men seems to have changed very little over this period. We attribute most of these trends to increases in separation and divorce rates and relative improvements in life expectancies for men. Lastly, with the exception of a discrete jump in the late 1970s, chronic illnesses seem to be relatively stable over time. We believe the discontinuity to be attributable to changing conventions rather than survey artifact. Furthermore, rates of illness are similar between the sexes, and unsurprisingly, the elderly are more likely to be chronically ill than the working-age.

Results from probit models applied to four sub-samples—working-age women, working-age men, elderly women, and elderly men—are reported in Tables IV–VII. In each table, regressions (1), (3), and (5) include a time trend, regressions (2) and (3) include a list effect, and regressions (4) and (5) include a list effect plus an interaction effect between chronic illness and list size. We test for the joint significance of the time trend and the list effect in regressions (3) and (5).

[Table IV about here]

[Table V about here]

[Table VI about here]

[Table VII about here]

The results for working-age women are reported in Table IV. Regression (1) highlights the persistent time trend after controlling for demographic and health characteristics. However, regression (2) shows that the time trend and the list effect are nearly interchangeable. The other parameter estimates and the precision of these estimates are negligibly different, but the overall model fit is slightly better in regression (2). Controlling for the time trend and demographic and health characteristics in regression (3), we find a negative association between the probabilities of visiting a public GP at least once in two weeks and list sizes among working-age women. Multicollinearity between the time trend and the list effect reduces the precision of the parameter estimates for both. We strongly reject joint insignificance, and furthermore, we continue to observe a statistically significant list effect. Regressions (4) and (5) have added an interaction effect between chronic illness and list size to regressions (2) and (3), respectively. The interaction term allows the list effect to vary according to health status. We find very modest evidence of a stronger list effect for the chronically ill, perhaps because they visit their GPs more often.

[Figure 5 about here]

The parameter estimates from regressions (4) and (5) give rise to the marginal list effects displayed with 95 percent confidence intervals in Figures 5a and 5b, respectively. With and without the time trend, the marginal effects are very similar, -0.009 and -0.008 on average, respectively. However, they are estimated with less precision in Figure 5b due to multicollinearity. Furthermore, the marginal list effects are stronger for smaller list sizes, and vice versa, which may be attributable to accounting for list size linearly and the shape of the normal distribution function. We would expect to observe weaker marginal effects for smaller list sizes, which raises the issue of accounting for list size nonlinearly. Although this is confirmed in Figure 6 when we include list size more flexibly, we cannot demonstrate that these effects are statistically different from their counterparts in Figure 5. Further note that our estimates are more precise for larger list sizes, which is again largely attributable to the curvature of the normal distribution function. In approximate terms, increasing list size by 100 decreases the probability of visiting a public GP at least once in two weeks by about 5.1 percent on average, given a predicted visit probability of 0.172 for working-age women.

[Figure 6 about here]

We highlight several further results for working-age women. There is a negative age effect, which is mainly attributable to a higher GP visit propensity during the childbearing years. Working-age women who are married and separated, divorced, or widowed are more likely to have visited a GP at least once in two weeks than are working-age women who have never married. As previously noted, working-age women who are suffering from a chronic illness are much more likely to have visited a GP at least once in two weeks.

The results for working-age men, elderly women, and elderly men are reported in Tables V–VII, respectively. We find little evidence of statistically significant list effects in these subsamples. However, there appears to be a statistically significant but very small positive list effect for working-age men, which we treat as negligible in conjunction with corresponding results in which list size is included nonlinearly. In addition, there appears to be a statistically significant and negative list effect for elderly women, but only when list size is specified nonlinearly.

For working-age men, there is a positive age effect, which is mainly attributable to a steadily higher GP visit propensity through the middle stages of life. Working-age men who are married and separated, divorced, or widowed are more likely to have visited a GP at least once in two weeks than are working-age men who have never married. Similar to working-age women, working-age men who are suffering from a chronic illness are much more likely to have visited a GP at least once in two weeks. For elderly women and men, there is a positive age effect. While it appears that elderly women and men who are married and separated, divorced, or widowed are more likely than their never married counterparts to have visited a GP at least once in two weeks, we cannot reject the hypotheses that these effects are equal, suggesting that having never been married is driving the results. Lastly, similar to their working-age counterparts, suffering from a chronic illness makes visiting a public GP at least once in two weeks more likely for elderly women and men.

4.2. *Pseudopanel Analysis*

In order to control for unobserved individual heterogeneity in the data, we need to follow the same individuals over time. To do this, we construct a pseudopanel, for which summary statistics are reported in Table VIII. As we move from left to right in Table VIII, we observe the cohorts aging. Unsurprisingly, they grow sicker and visit their GPs more often. Results from GP visit regressions applied to both women and men are reported in Tables IX and X, respectively. Regressions (1) and (5) in both tables correspond to pooled OLS, while regressions (2)–(4) and (6) control for cohort fixed effects and age fixed effects. Cohort fixed effects are captured by including cohort dummy variables, which is least squares dummy variables (LSDV) estimation. The results from LSDV and WG estimation are identical, with the exception of a higher R-squared in the former and greater degrees of freedom in the latter. Age fixed effects are captured by including sample means of age dummies for each cell, which may help to smooth any age effects (see Parkin et al. (1999)).

[Table VIII about here]

[Table IX about here]

[Table X about here]

Regression (1) in Table IX simply highlights the negative correlation over the life cycle between list sizes and the number of GP visits for women. Introducing cohort and age fixed effects in regressions (2)–(4) has little impact on these correlations, with the exception of reducing the precision of the estimate in regression (4). However, introducing further controls in regressions (5) and (6) reduces the list effects considerably, and in regression (6), leaves no significant role for list sizes in the explanation of GP visits for women. GP visits for women are heavily determined by being chronic ill, especially in the presence of cohort and age fixed effects. These effects are less robust due to their correlations with marital status and health status.

Similarly, regression (1) in Table X highlights the negative correlation over the life cycle between list sizes and the number of GP visits for men. The raw correlation is stronger for men than for women. Introducing cohort fixed effects in regression (2) has little impact on this correlation, but introducing age fixed effects in regression (3) weakens it substantially and also reduces the precision of the estimate. Introducing both cohort fixed effects and age fixed effects in regression (4) leaves no significant role for list sizes in the explanation of GP visits for men. Further controlling for marital status and health status in regressions (5) and (6) shows that GP visits for men are largely driven by being separated, divorced, or widowed as well as chronically ill. As with women, the cohort and age fixed effects are less robust in the presence of regressors with which they are correlated.

[Table XI about here]

Correlations based on total variation as well as residual variation after eliminating cohort-specific fixed effects are presented in Table XI. For both women and men, list sizes are highly negatively correlated with being separated, divorced, or widowed, as well as being chronically ill. This may be evidence of an endogeneity problem. If, taking the latter as an example, the chronically ill are more likely to visit their GPs, which in turn causes GPs to shift to areas of high demand and consequently reduces list sizes, then the assumption of exogenous list sizes, currently identifying demand responses to congestion, is obviously violated. We leave this problem as a subject of future research.

[Figure 7 about here]

The results in Tables IX and X are perhaps best interpreted in relation to Figure 7. As we move from left to right in this figure, we follow the youngest cohorts as they age until they overlap with the next youngest cohorts. We then follow these cohorts as they age, and so on. The upper plot corresponds to GP visits for women, and the lower plot to GP visits for men. We have already seen in Figure 1 that working-age women and the elderly have similar visit patterns, but that working-age men follow a different trend. Figure 7 provides some insight. Women visit their GPs more than men during their childbearing years. The number of visits increases for women through their 20s and peaks around age 30, after which it declines until the mid-40s. For men, the number of GP visits is lower and flatter until about age 40, after which it steadily increases. Men and women have approximately the same visit frequencies by age 45, after which they increase together through the middle and late stages of life.

Taken altogether, we conclude that GP visits are largely driven by health status, and for women, by pregnancy and childbirth. The list effects that arise in the pooled regressions in are eliminated by allowing for sufficient controls. Introducing cohort and age fixed effects is enough to trivialize the result for men, but not women. Further introducing controls for marital status and health status trivializes the result for women. We would also like to include controls for pregnancy, but the GHS does not provide this information. Furthermore, we are missing information on income and education since the GHS does not reliably provide these data over the period of study. Future research should consider drawing upon other sources to supplement the existing pseudopanel.

5. CONCLUSIONS

Since the mid-1970s GP visits under the NHS have increased in England, both per person and in the aggregate. These increases are robust to adjustments for changes in demographic and health characteristics. The number of GPs has increased as well, and at a rate faster than that at which the population has grown. Consequently, list sizes have decreased since the mid-1970s. Without an explicit price mechanism in the public sector, GP visit rates vary with other factors, which may include waiting times, instrumented for by list sizes.

We find a negative association between the probabilities of visiting a public GP at least once in two weeks and list sizes only among working-age women. We also find strong positive associations between these probabilities and chronic illnesses among the working-age and elderly, women and men alike. However, using a pseudopanel from 1974 to 2004, we conclude that waiting times, instrumented for by list sizes, have little to no effect on the demand for GP visits. GP visit rates are largely driven by health status, and for women, by pregnancy and childbirth.

APPENDIX A: DATA APPENDIX

The data on individuals are from the GHS from 1974 to 2004. The household questions are addressed to the household reference person, capturing information on demographics, family structure, accommodation, housing tenure, ownership of consumer durables, migration, and income. The individual questions are addressed to all individuals 16 and older within each household, capturing information on employment, pensions, education, health, the use of health services, fertility, and income.

The GP visit variable is derived from answers to a series of questions: (1) "During the 2 weeks ending yesterday, apart from any visit to a hospital, did you talk to a doctor for any reason at all, either in person or by telephone?", (2) "How many times did you talk to a doctor in these 2 weeks?", (3) "On whose behalf was this consultation made?", (4) "Was this consultation under the National Health Service or paid for privately?", (5) "Was the doctor a GP (ie a family doctor) or some other kind of doctor?", and (6) "Did you talk to the doctor by telephone, at your home, in the doctor's surgery, at a health centre, or elsewhere?". This particular survey question is from 2004, but the wording largely remains the same over the period we study. We first verify the internal consistency of each respondent's answers, prioritizing question (1) ahead of question (2). We then ensure that consultations are made with GPs under the NHS solely on the behalves of the respondents. Lastly, we exclude consultations by telephone and at home. With these restrictions imposed, the GP visit variables are the number of GP visits over a two-week period or the corresponding dummy variable equal to one if an individual has visited a GP at least once in two weeks and zero otherwise.

The chronic illness variable equals one if an individual has answered "yes" to the following question and zero otherwise: "Do you have any long-standing illness, disability or infirmity? By long-standing, I mean anything that has troubled you over a period of time or that is likely to affect you over a period of time?". This particular survey question is from 2004, but the wording again varies little over the period we study.

The data on GPs are from the DoH and the NHS IC. The DoH and IC provide the number of GPs and the number of registered patients in a given area. Between 1974 and 1991, the number of GPs is equal to the number of unrestricted principals, and between 1992 and 2004, the number of GPs is equal to the number of GPs (contracted or other) under General Medical Services (GMS) and Personal Medical Services (PMS). Between 1974 and 1991, the data are provided according to Regional Health Authority (RHA), which corresponds to Northern, Yorkshire, Trent, East Anglian, North West Thames, North East Thames, South East Thames, South West Thames, Wessex, Oxford, South Western, West Midlands, Mersey, or North Western. Between 1992 and 2004, the data are provided according to Strategic Health Authority (SHA), which corresponds to North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South

East Coast, South Central, or South West. In order to link this information to each individual in the GHS sample, we map from RHA/SHA to GOR, which corresponds to Northeast, Northwest, Yorkshire and the Humberside, East Midlands, West Midlands, East, London, Southeast, or Southwest. The mapping is provided in Table XII.

[Table XII about here]

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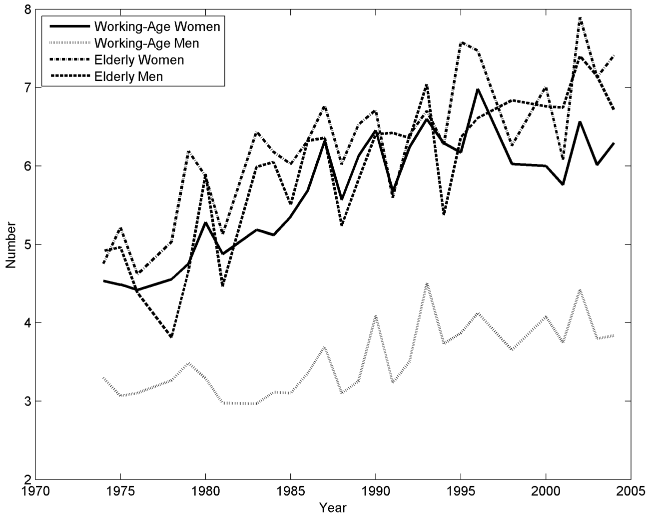


Figure 1: Annual GP Visits Per Person

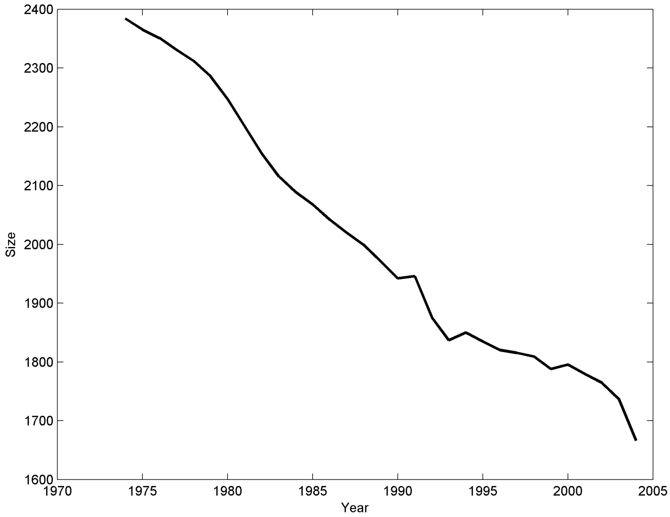
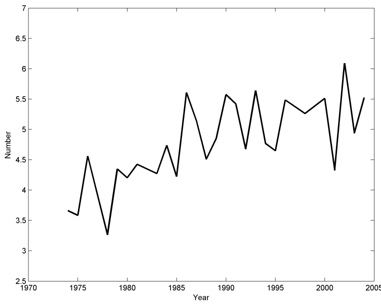
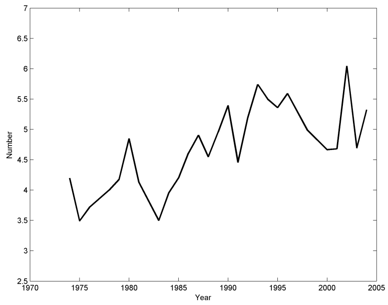


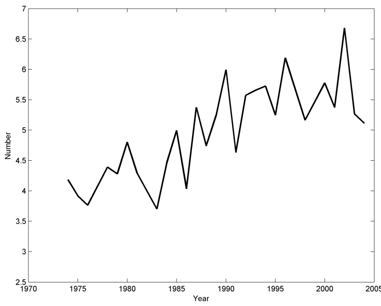
Figure 2: List Sizes



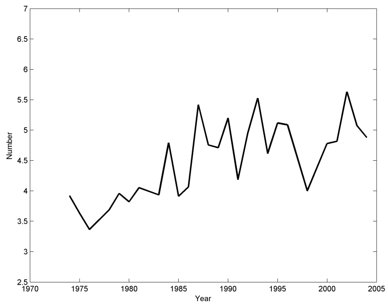
(a) Northeast



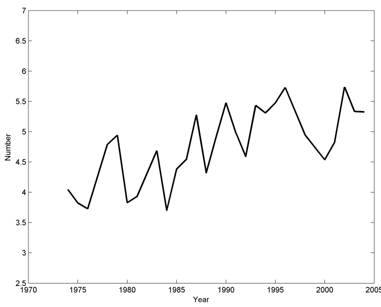
(b) Northwest



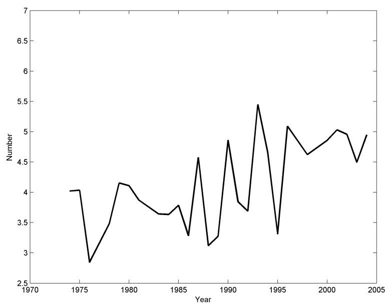
(c) Yorkshire and the Humberside



(d) East Midlands

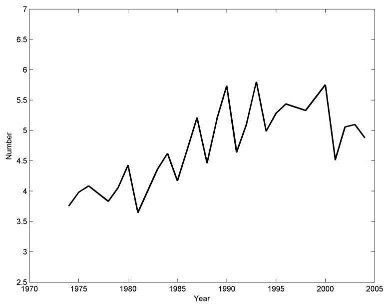


(e) West Midlands

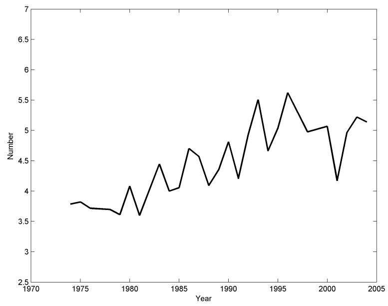


(f) East

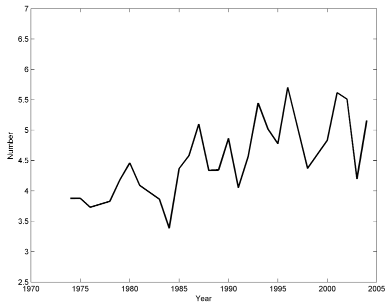
Figure 3: Annual GP Visits Per Person by Region



(g) London

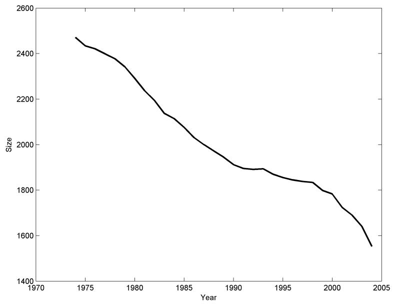


(h) Southeast



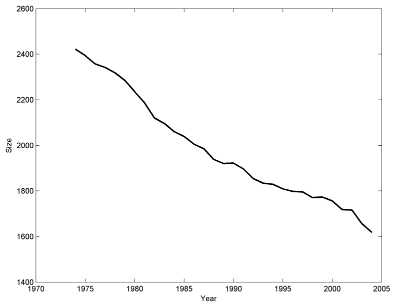
(i) Southwest

Figure 3: (Continued)

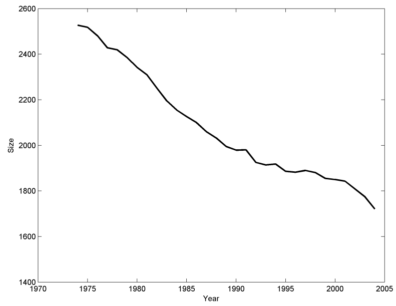


(a) Northeast

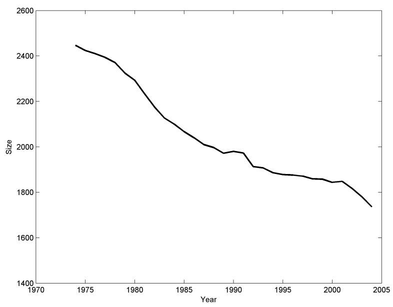
(b) Northwest



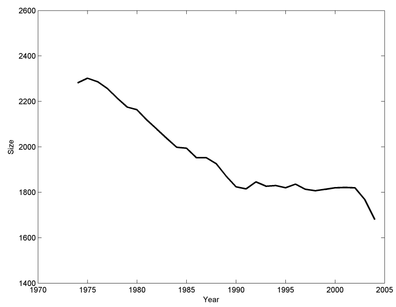
(c) Yorkshire and the Humberside



(d) East Midlands

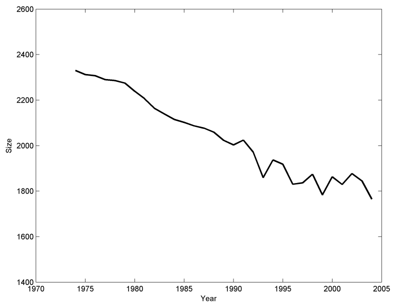


(e) West Midlands

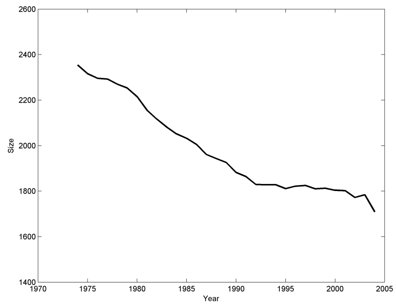


(f) East

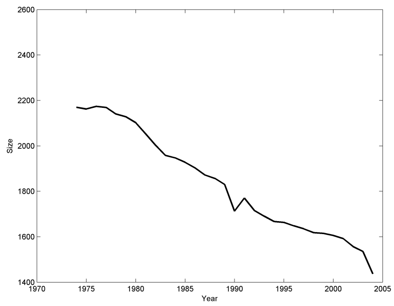
Figure 4: List Sizes by Region



(g) London

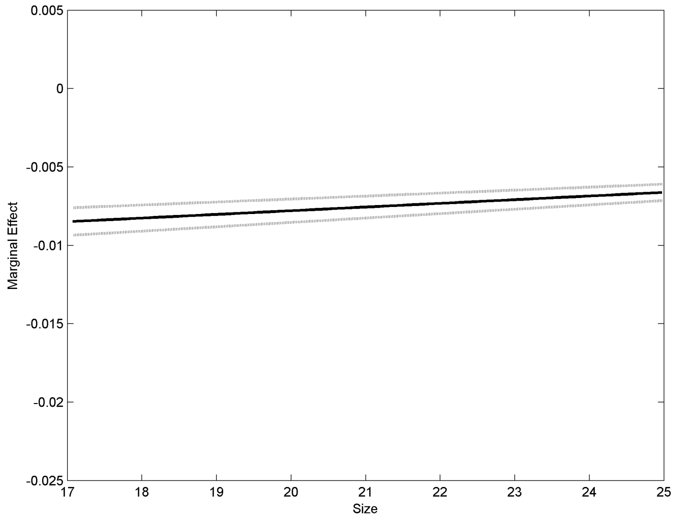


(h) Southeast

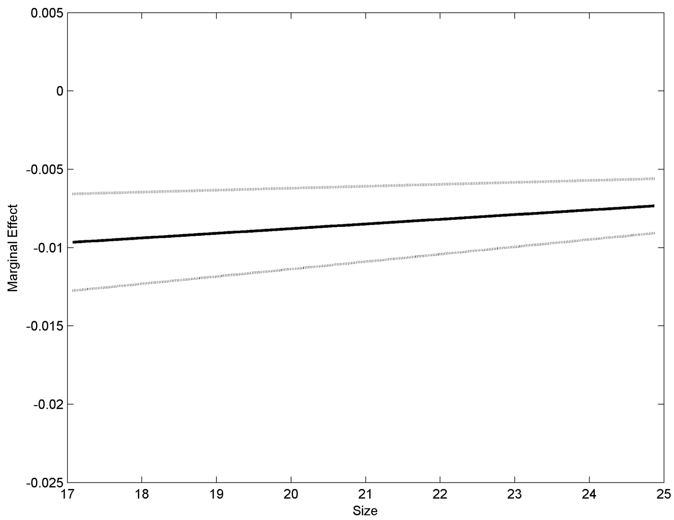


(i) Southwest

Figure 4: (Continued)

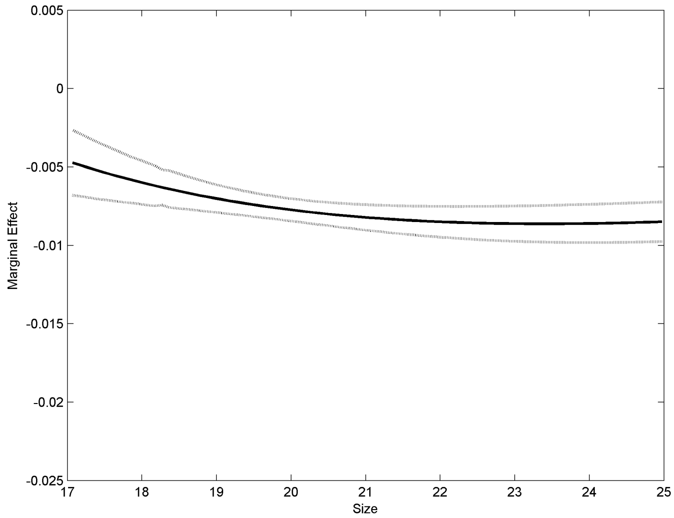


(a) Without Time Trend

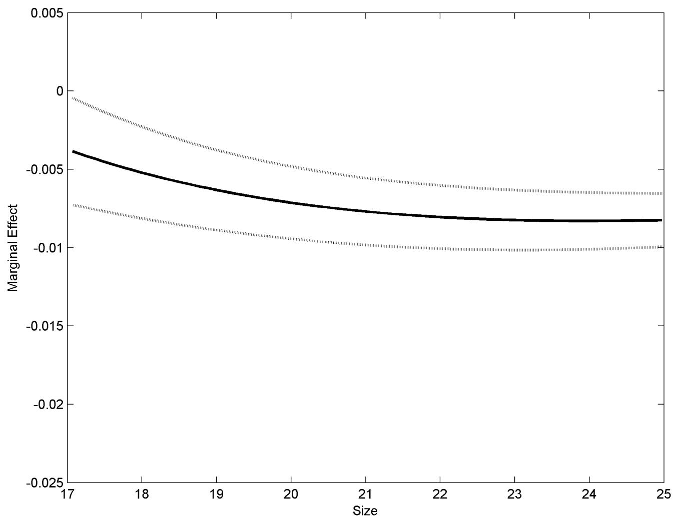


(b) With Time Trend

Figure 5: List Effects for Working-Age Women



(a) Without Time Trend



(b) With Time Trend

Figure 6: Flexible List Effects for Working-Age Women

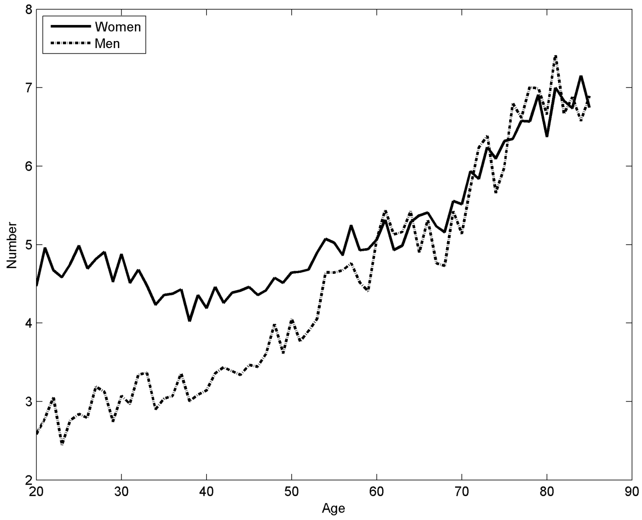


Figure 7: Annual GP Visits Over the Life Cycle

Table I:
Data Structure

Cohort	Year of Birth	Sex	Region	Mean Cell Size
1	1949–1958	Female	Northeast	97
2	1949–1958	Female	Northwest	201
3	1949–1958	Female	Yorkshire and the Humberside	150
4	1949–1958	Female	East Midlands	124
5	1949–1958	Female	West Midlands	162
6	1949–1958	Female	East	81
7	1949–1958	Female	London	211
8	1949–1958	Female	Southeast	309
9	1949–1958	Female	Southwest	137
10	1949–1958	Male	Northeast	91
11	1949–1958	Male	Northwest	191
12	1949–1958	Male	Yorkshire and the Humberside	149
13	1949–1958	Male	East Midlands	118
14	1949–1958	Male	West Midlands	157
15	1949–1958	Male	East	76
16	1949–1958	Male	London	198
17	1949–1958	Male	Southeast	200
18	1949–1958	Male	Southwest	127
19	1939–1948	Female	Northeast	90
20	1939–1948	Female	Northwest	195
21	1939–1948	Female	Yorkshire and the Humberside	143
22	1939–1948	Female	East Midlands	120
23	1939–1948	Female	West Midlands	156
24	1939–1948	Female	East	81
25	1939–1948	Female	London	173
26	1939–1948	Female	Southeast	311
27	1939–1948	Female	Southwest	138
28	1939–1948	Male	Northeast	88
29	1939–1948	Male	Northwest	187
30	1939–1948	Male	Yorkshire and the Humberside	139
31	1939–1948	Male	East Midlands	119

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Cohort	Year of Birth	Sex	Region	Mean Cell Size
32	1939–1948	Male	West Midlands	153
33	1939–1948	Male	East	82
34	1939–1948	Male	London	164
35	1939–1948	Male	Southeast	300
36	1939–1948	Male	Southwest	132
37	1929–1938	Female	Northeast	84
38	1929–1938	Female	Northwest	161
39	1929–1938	Female	Yorkshire and the Humberside	121
40	1929–1938	Female	East Midlands	97
41	1929–1938	Female	West Midlands	130
42	1929–1938	Female	East	62
43	1929–1938	Female	London	145
44	1929–1938	Female	Southeast	239
45	1929–1938	Female	Southwest	113
46	1929–1938	Male	Northeast	76
47	1929–1938	Male	Northwest	154
48	1929–1938	Male	Yorkshire and the Humberside	114
49	1929–1938	Male	East Midlands	96
50	1929–1938	Male	West Midlands	129
51	1929–1938	Male	East	61
52	1929–1938	Male	London	138
53	1929–1938	Male	Southeast	230
54	1929–1938	Male	Southwest	109
55	1919–1928	Female	Northeast	84
56	1919–1928	Female	Northwest	157
57	1919–1928	Female	Yorkshire and the Humberside	120
58	1919–1928	Female	East Midlands	93
59	1919–1928	Female	West Midlands	127
60	1919–1928	Female	East	60
61	1919–1928	Female	London	143
62	1919–1928	Female	Southeast	233
63	1919–1928	Female	Southwest	118
64	1919–1928	Male	Northeast	74
65	1919–1928	Male	Northwest	136
66	1919–1928	Male	Yorkshire and the Humberside	106

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Cohort	Year of Birth	Sex	Region	Mean Cell Size
67	1919–1928	Male	East Midlands	84
68	1919–1928	Male	West Midlands	116
69	1919–1928	Male	East	54
70	1919–1928	Male	London	124
71	1919–1928	Male	Southeast	204
72	1919–1928	Male	Southwest	100

TABLE II

GP VISITS, SUPPLY, AND WORKLOAD

'74–'79	'80–'84	'85–'89	'90–'94	'95–'99	'00–'04	Δ/year	%Δ/year
			Annual GP Visits Per Person				
4.12	4.73	4.82	5.25	5.27	5.07	0.038**	0.82**
			Registered Patients (Millions)				
48.44	49.16	50.22	49.91	50.79	51.87	0.124**	0.25**
			Annual GP Visits (Millions)				
199.68	231.10	242.05	261.99	266.59	263.19	2.491**	1.07**
			Registered GPs				
20,723	22,759	24,869	26,420	28,008	29,696	352.556**	1.41**
			List Sizes				
2,339	2,161	2,019	1,889	1,821	1,747	−23.526**	−1.16**
			Annual Visits Per GP				
9,642	10,157	9,733	9,916	9,575	8,863	−32.024*	−0.34*

Notes: Changes and percentage changes are the parameter estimates obtained from a linear regression model.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

Table III: Summary Statistics

Characteristics	'74–'79	'80–'84	'85–'89	'90–'94	'95–'99	'00–'04	Δ/year	%Δ/year
Age								
Working-Age Women	39.835	39.146	38.934	39.228	39.928	40.571	0.035**	0.09**
Working-Age Men	39.271	38.704	38.860	39.273	39.916	40.755	0.065**	0.16**
Elderly Women	74.101	74.359	74.870	75.161	75.116	75.268	0.047**	0.06**
Elderly Men	72.647	73.137	73.558	73.848	74.021	74.242	0.061**	0.08**
Married								
Working-Age Women	0.727	0.694	0.649	0.606	0.588	0.547	−0.007**	−1.12**
Working-Age Men	0.725	0.684	0.640	0.605	0.588	0.552	−0.007**	−1.05**
Elderly Women	0.345	0.372	0.373	0.391	0.416	0.445	0.004**	0.93**
Elderly Men	0.721	0.735	0.723	0.712	0.702	0.705	−0.001**	−0.14**
Separated, Divorced, or Widowed								
Working-Age Women	0.102	0.110	0.112	0.123	0.129	0.125	0.001**	0.83**
Working-Age Men	0.039	0.046	0.052	0.058	0.064	0.068	0.001**	2.11**
Elderly Women	0.539	0.522	0.537	0.532	0.521	0.496	−0.001**	−0.26**
Elderly Men	0.225	0.215	0.218	0.222	0.236	0.227	0.000	0.16
Chronic Illness								
Working-Age Women	0.244	0.302	0.313	0.314	0.314	0.305	0.002**	0.69**
Working-Age Men	0.249	0.300	0.310	0.313	0.3264	0.307	0.002**	0.71**
Elderly Women	0.578	0.641	0.650	0.625	0.611	0.617	0.001	0.09
Elderly Men	0.525	0.574	0.600	0.610	0.601	0.625	0.003	0.59**

Notes: Changes and percentage changes are the parameter estimates obtained from a linear regression model.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

TABLE IV

Probit Estimates for Working-Age Women

	(1)	(2)	(3)	(4)	(5)
Year	0.007**		−0.001		−0.001
	(17.81)		(0.68)		(0.71)
Age	−0.008**	−0.008**	−0.008**	−0.008**	−0.008**
	(34.92)	(35.93)	(34.46)	(34.49)	(33.12)
Married	0.155**	0.154**	0.154**	0.154**	0.153**
	(20.95)	(20.83)	(21.30)	(20.87)	(21.35)
Separated, Divorced,	0.223**	0.222**	0.222**	0.222**	0.221**
or Widowed	(20.10)	(19.98)	(20.26)	(20.10)	(20.37)
Chronic Illness	0.490**	0.489**	0.489**	0.701**	0.701**
	(48.20)	(48.08)	(47.93)	(6.50)	(6.50)
List Size / 100		−0.032**	−0.035**	−0.028**	−0.032**
		(20.20)	(6.57)	(13.61)	(6.77)
Chronic Illness				−0.011	−0.011
× List Size / 100				(1.91)	(1.91)
Constant	−1.006**	−0.252**	−0.161	−0.326**	−0.230*
	(66.08)	(7.16)	(1.30)	(6.83)	(2.10)
Regional Controls?	Yes	Yes	Yes	Yes	Yes
Test ($\chi^2(2)$)			427.89**		301.91**
Observations	180,564	180,564	180,564	180,564	180,564
Log Likelihood	−80,598	−80,583	−80,582	−80,578	−80,577

Notes: The dependent variable equals one if an individual has visited a GP at least once in two weeks and zero otherwise. Point estimates are the parameter estimates obtained from a probit model. Absolute values of z-statistics corresponding to standard errors adjusted for GOR clusters are in parentheses. The year is zeroed in 1974. The excluded marital status is never married. Regional controls correspond to GORs. The Wald test is for joint significance of the list and year effects.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

TABLE V

Probit Estimates for Working-Age Men

	(1)	(2)	(3)	(4)	(5)
Year	0.004**		0.007**		0.007**
	(10.40)		(5.54)		(5.52)
Age	0.003**	0.003**	0.003**	0.003**	0.003**
	(8.66)	(8.94)	(8.56)	(8.98)	(8.59)
Married	0.030**	0.028**	0.031**	0.028**	0.030**
	(3.37)	(3.10)	(3.41)	(3.03)	(3.33)
Separated, Divorced,	0.101**	0.100**	0.101**	0.100**	0.100**
or Widowed	(5.09)	(5.05)	(5.10)	(4.98)	(5.04)
Chronic Illness	0.565**	0.565**	0.566**	0.673**	0.673**
	(39.86)	(39.78)	(39.74)	(7.21)	(7.25)
List Size / 100		−0.015**	0.014*	−0.013**	0.016**
		(6.95)	(2.20)	(5.30)	(2.68)
Chronic Illness				−0.005	−0.005
× List Size / 100				(1.15)	(1.14)
Constant	−1.647**	−1.273**	−1.988**	−1.317**	−2.031**
	(79.28)	(23.04)	(12.93)	(21.90)	(13.90)
Regional Controls?	Yes	Yes	Yes	Yes	Yes
Test ($\chi^2(2)$)			395.95**		86.58**
Observations	171,477	171,477	171,477	171,477	171,477
Log Likelihood	−56,376	−56,383	−56,374	−56,382	−56,373

Notes: The dependent variable equals one if an individual has visited a GP at least once in two weeks and zero otherwise. Point estimates are the parameter estimates obtained from a probit model. Absolute values of z-statistics corresponding to standard errors adjusted for GOR clusters are in parentheses. The year is zeroed in 1974. The excluded marital status is never married. Regional controls correspond to GORs. The Wald test is for joint significance of the list and year effects.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

TABLE VI

PROBIT ESTIMATES FOR ELDERLY WOMEN

	(1)	(2)	(3)	(4)	(5)
Year	0.008^{**}		0.006		0.006
	(11.06)		(1.49)		(1.46)
Age	0.004^{*}	0.004^{*}	0.004^{*}	0.004^{*}	0.004^{*}
	(2.29)	(2.28)	(2.28)	(2.28)	(2.28)
Married	0.110^{**}	0.111^{**}	0.110^{**}	0.110^{**}	0.109^{**}
	(3.22)	(3.30)	(3.22)	(3.27)	(3.20)
Separated, Divorced,	0.108^{**}	0.108^{**}	0.108^{**}	0.108^{**}	0.107^{**}
or Widowed	(3.07)	(3.12)	(3.08)	(3.09)	(3.06)
Chronic Illness	0.453^{**}	0.451^{**}	0.452^{**}	-0.046	-0.041
	(29.46)	(29.09)	(30.08)	(0.35)	(0.31)
List Size / 100		-0.032^{**}	-0.009	-0.050^{**}	-0.027
		(13.13)	(0.58)	(12.28)	(1.53)
Chronic Illness				0.025^{**}	0.025^{**}
$\times$ List Size / 100				(3.75)	(3.73)
Constant	-1.671^{**}	-0.894^{**}	-1.456^{**}	-0.554^{**}	-1.103^{*}
	(11.26)	(4.74)	(3.45)	(2.77)	(2.44)
Regional Controls?	Yes	Yes	Yes	Yes	Yes
Test ($\chi^2(2)$)			157.33^{**}		158.28^{**}
Observations	$46,535$	$46,535$	$46,535$	$46,535$	$46,535$
Log Likelihood	$-22,482$	$-22,484$	$-22,482$	$-22,477$	$-22,475$

Notes: The dependent variable equals one if an individual has visited a GP at least once in two weeks and zero otherwise. Point estimates are the parameter estimates obtained from a probit model. Absolute values of z-statistics corresponding to standard errors adjusted for GOR clusters are in parentheses. The year is zeroed in 1974. The excluded marital status is never married. Regional controls correspond to GORs. The Wald test is for joint significance of the list and year effects.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

TABLE VII

Probit Estimates for Elderly Men

	(1)	(2)	(3)	(4)	(5)
Year	0.008**		0.004		0.004
	(7.02)		(0.89)		(0.91)
Age	0.008**	0.008**	0.008**	0.008**	0.008**
	(4.64)	(4.63)	(4.62)	(4.64)	(4.63)
Married	0.087**	0.087**	0.087**	0.087**	0.087**
	(3.27)	(3.28)	(3.27)	(3.30)	(3.29)
Separated, Divorced,	0.078*	0.077*	0.078*	0.077*	0.077*
or Widowed	(2.43)	(2.44)	(2.44)	(2.45)	(2.45)
Chronic Illness	0.462**	0.461**	0.461**	0.159	0.157
	(19.33)	(19.46)	(19.47)	(0.95)	(0.95)
List Size / 100		−0.032**	−0.015	−0.043**	−0.025
		(6.46)	(0.80)	(4.73)	(1.28)
Chronic Illness				0.015	0.015
× List Size / 100				(1.77)	(1.79)
Constant	−1.966**	−1.185**	−1.601**	−0.983**	−1.405**
	(13.28)	(7.07)	(3.10)	(4.41)	(2.71)
Regional Controls?	Yes	Yes	Yes	Yes	Yes
Test ($\chi^2(2)$)			48.41**		24.44**
Observations	32,794	32,794	32,794	32,794	32,794
Log Likelihood	−15,290	−15,290	−15,289	−15,288	−15,287

Notes: The dependent variable equals one if an individual has visited a GP at least once in two weeks and zero otherwise. Point estimates are the parameter estimates obtained from a probit model. Absolute values of z-statistics corresponding to standard errors adjusted for GOR clusters are in parentheses. The year is zeroed in 1974. The excluded marital status is never married. Regional controls correspond to GORs. The Wald test is for joint significance of the list and year effects.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

TABLE VIII

SUMMARY STATISTICS

Variables	'74–'79	'80–'84	'85–'89	'90–'94	'95–'99	'00–'04
Women						
Number of GP Visits	4.546	4.983	5.372	6.019	6.388	6.594
	(1.157)	(1.273)	(1.330)	(1.257)	(1.645)	(1.648)
List Size / 100	23.457	21.515	19.978	18.786	18.217	17.413
	(1.029)	(0.954)	(0.710)	(0.829)	(0.715)	(0.990)
Age	37.445	43.460	48.358	53.404	57.653	63.253
	(11.375)	(11.358)	(11.347)	(11.328)	(11.302)	(11.200)
Married	0.781	0.803	0.761	0.705	0.659	0.606
	(0.145)	(0.077)	(0.083)	(0.103)	(0.124)	(0.157)
Separated, Divorced,	0.079	0.127	0.165	0.215	0.263	0.318
or Widowed	(0.045)	(0.068)	(0.086)	(0.106)	(0.134)	(0.171)
Chronic Illness	0.219	0.327	0.381	0.427	0.466	0.516
	(0.085)	(0.117)	(0.125)	(0.127)	(0.130)	(0.131)
Men						
Number of GP Visits	3.100	3.318	3.736	4.453	5.067	5.911
	(0.956)	(1.180)	(1.364)	(1.642)	(1.998)	(1.976)
List Size / 100	23.457	21.515	19.978	18.786	18.217	17.413
	(1.029)	(0.954)	(0.710)	(0.829)	(0.715)	(0.990)
Age	37.432	43.437	48.363	53.343	57.595	63.186
	(11.386)	(11.331)	(11.316)	(11.280)	(11.231)	(11.095)
Married	0.752	0.817	0.810	0.785	0.769	0.734
	(0.215)	(0.086)	(0.056)	(0.055)	(0.064)	(0.070)
Separated, Divorced,	0.036	0.056	0.078	0.098	0.125	0.161
or Widowed	(0.023)	(0.028)	(0.039)	(0.044)	(0.060)	(0.085)
Chronic Illness	0.228	0.328	0.382	0.433	0.480	0.530
	(0.082)	(0.114)	(0.136)	(0.138)	(0.127)	(0.134)

Notes: Point estimates are means. Standard deviations are in parentheses.

TABLE IX

GP Visit Regressions for Women

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	11.236**	12.283**	11.402*	10.393	11.713**	6.758
	(18.02)	(18.90)	(2.13)	(1.98)	(15.81)	(1.25)
List Size / 100	−0.279**	−0.324**	−0.311**	−0.274**	−0.201**	−0.118
	(9.10)	(9.94)	(10.42)	(3.59)	(6.82)	(1.46)
Married					−3.138**	1.197
					(6.21)	(0.55)
Separated, Divorced,					−1.389	1.903
or Widowed					(1.67)	(0.82)
Chronic Illness					1.324	4.990**
					(1.51)	(4.59)
Cohort Effects?	No	Yes	No	Yes	No	Yes
Age Effects?	No	No	Yes	Yes	No	Yes
Observations	936	936	936	936	936	936
R-Squared	0.169	0.261	0.297	0.390	0.228	0.414

Notes: The dependent variable is the number of annual GP visits per cohort. Point estimates are the parameter estimates obtained from a linear regression model. Absolute values of t-statistics corresponding to standard errors adjusted for cohort clusters are in parentheses. The excluded marital status is never married. Observations are weighted by the square roots of the cohort sizes.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

TABLE X

GP Visit Regressions for Men

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	11.655**	12.025**	10.508**	7.153*	2.543**	6.105
	(14.72)	(19.31)	(3.71)	(2.38)	(7.15)	(1.99)
List Size / 100	−0.377**	−0.430**	−0.125**	0.061	−0.016	0.140
	(11.18)	(13.77)	(5.41)	(0.78)	(1.19)	(1.77)
Married					−1.350**	0.171
					(4.77)	(0.11)
Separated, Divorced,					6.557**	4.671**
or Widowed					(4.84)	(2.84)
Chronic Illness					6.338**	3.601**
					(15.28)	(3.99)
Cohort Effects?	No	Yes	No	Yes	No	Yes
Age Effects?	No	No	Yes	Yes	No	Yes
Observations	936	936	936	936	936	936
R-Squared	0.215	0.504	0.560	0.613	0.568	0.627

Notes: The dependent variable is the number of annual GP visits per cohort. Point estimates are the parameter estimates obtained from a linear regression model. Absolute values of t-statistics corresponding to standard errors adjusted for cohort clusters are in parentheses. The excluded marital status is never married. Observations are weighted by the square roots of the cohort sizes.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

TABLE XI

Correlations

	GP	LIST	MAR	SDW	SICK
Women					
	GP	LIST	MAR	SDW	SICK
GP	1.000				
LIST	−0.409	1.000			
MAR	−0.389	0.396	1.000		
SDW	0.385	−0.526	−0.828	1.000	
SICK	0.385	−0.576	−0.596	0.832	1.000
	GP	LIST	MAR	SDW	SICK
GP	1.000				
LIST	−0.472	1.000			
MAR	−0.434	0.559	1.000		
SDW	0.503	−0.782	−0.833	1.000	
SICK	0.526	−0.865	−0.595	0.742	1.000
Men					
	GP	LIST	MAR	SDW	SICK
GP	1.000				
LIST	−0.445	1.000			
MAR	−0.105	0.033	1.000		
SDW	0.644	−0.540	−0.226	1.000	
SICK	0.700	−0.571	0.061	0.733	1.000
	GP	LIST	MAR	SDW	SICK
GP	1.000				
LIST	−0.561	1.000			
MAR	−0.271	0.082	1.000		
SDW	0.554	−0.701	−0.399	1.000	
SICK	0.605	−0.856	−0.206	0.653	1.000

Notes: Upper sets of correlations are based on total variation, and lower sets on residual variation after eliminating cohort-specific fixed effects. In relation to previous tables, GP is Number of GP Visits, LIST is List Size / 100, MAR is Married, SDW is Separated, Divorced, or Widowed, and SICK is Chronic Illness.

TABLE XII

Health Authority and Regional Correspondence

GOR	RHA	SHA
Northeast	Northern	North East
Northwest	Mersey	North West
	North Western	
Yorkshire and the Humberside	Yorkshire	Yorkshire and the Humber
East Midlands	Trent	East Midlands
West Midlands	West Midlands	West Midlands
East	East Anglian	East of England
London	North West Thames	London
	North East Thames	
	South East Thames	
	South West Thames	
Southeast	Wessex	South East Coast
	Oxford	South Central
Southwest	South Western	South West